4.0 Impacts of Variability on Agriculture

4.1 Introduction

Crop yield variability is the result of many different factors. These factors include changing production practices such as the introduction of new tools, new hybrids and varieties or cultivars, development of new diseases and pests, and government policy. Underlying many of these factors are extreme weather events and the variability of the weather from year-to-year. Extreme weather events like hurricanes and droughts have obvious impacts and recently necessitated two disaster relief bills for farmers. In the past decade large yield reductions were observed in 1988 due to the severe drought throughout the mid-section of the United States, and again in 1993 when large areas of Illinois, Iowa, Missouri and other mid-western states experienced record rainfall from early spring through summer. In the early 1980's corn surpluses were so large that in 1983 farmers were paid to remove large acreage from production. In recent years climate scientists have improved their ability to identify and predict 6 to 18 months in advance seasonal-to-interannual climate phenomena, like the El Niño Southern Oscillation (ENSO). This improved prediction capability has contributed to increased attention toward identifying how farmers would or could respond in anticipation of these events. A number of studies suggest that perhaps 1/5 of the losses related to such events could be avoided if appropriate changes in cropping practices were made.

In this chapter, we review and evaluate the impacts of climate variability on crop yields and consequent impact on the US agricultural economy, focusing primarily on how greenhouse gas induced climate change could change variability. We first present the method by which the climate change scenarios were used in results discussed in chapter 3 and later in this chapter. The purpose is to make clear the extent to which the approach already includes variability and extreme events as they affect agriculture. We also clarify the relationship between changes in the mean of climate, the variability of climate, and the frequency of climatic extremes.

The basic approach in the core site studies in Chapter 3 was to apply changes in mean monthly precipitation and temperature from the GCM scenarios to actual 30-year historical records for the sites. The PNNL approach used changes from the GCMs as seeds for a stochastic weather generator that is part of their model. Both approaches thereby include variable weather. For temperature in the site studies, the absolute differences between the GCM-modeled mean monthly temperature in the scenario with greenhouse gas forcing and the GCM modeled climate without forcing (often referred to as the control scenario) were calculated. These differences were added to the daily values of the historical record for each site for the applicable month for the 30-year historical record. In doing so, the variability of weather remains the same as in the historical record, but the mean is higher.

For precipitation, the standard approach is to use ratios of the GHG-forced climate and the control climate, rather than absolute differences, to avoid the possibility of obtaining negative precipitation values. Negative values could occur if differences between the future and current climate model results were negative and were added to smaller observed precipitation amounts. This approach changes the variability of the daily intensity of precipitation. The variance changes as a function of the square of the ratio of the climate change to control climate projections. Mearns et al., 1996). This change in variance is only the coincidental result of using ratios rather than differences and does not reflect an analysis of how variability might actually change based on analysis of GCM results. The PNNL stochastic weather generator also reproduces weather that varies like that observed in the past but the stochastic aspect of the approach means that the realized weather has characteristics like historical weather but is different in each run. The mean and variance calculated over many years of simulation is the same across runs. These approaches have been developed because the climate model results are still too inaccurate on a regional scale to be used directly.

The method used here for generating climate input for the crop models thus produces a weather record with climate change that includes storms, droughts, and extreme temperatures. In particular since monthly mean changes were used, the seasonality of climate can change (e.g., distribution of precipitation and the pattern of warming over the year). For example, if the GCM scenario predicts a precipitation decrease of 90 percent in the summer and a precipitation increase of 90 percent in the winter for a location with seasonally balanced precipitation, then the yearly total precipitation would not change but the seasonal distribution would be greatly altered. This can be viewed as a change in the seasonal cycle (seasonal variability) of precipitation. This change is captured by methods applied in Chapter 3.

Changing the mean temperature and precipitation in this way also changes the frequency of extremes, say, the likelihood of the maximum temperature on any day in the summer exceeding 35° C. In fact, given the usual distribution of temperature highs for a day, the frequency of exceeding an absolute threshold such as 35°C changes rapidly with a change in the mean. For example, based on the 30-year weather record for Des Moines, Iowa, there currently is an 11 percent chance of the maximum temperature on any day in summer exceeding 35° C. And based on the distribution of high temperatures for Des Moines, if the mean temperature were to increase by 1.7° C the chance of exceeding 35° C would rise to 22 percent. Thus, for a relatively small change in the mean maximum temperature the likelihood of exceeding 35° C doubles. Again, this increase in the likelihood of extremes is captured in the methods applied in Chapter 3 and later in this Chapter.

If the variability (i.e., standard deviation or variance) of the temperature also changed, this would further affect the frequency of the extreme events. For example, if the simulated distribution of highs became wider (i.e. the variance increased), then the chance of exceeding 35° C in the above example would increase by more than 22 percent. This aspect of change in variability was not incorporated in our scenarios. Similarly some aspects of potential changes in variability in precipitation are excluded as a result of the methods applied in Chapter 3. For example, if the historical record has on average 10 rain events in July and August, the climate change scenario developed using the method in Chapter 3 also will have, on average, 10 rain events in July and August. The method also does not account for changes in frequency of precipitation on a daily time scale. So, the result of GCM predictions of an increase in precipitation is that each rain event has more rain. But, the method used in Chapter 3 would not include a predicted trend toward fewer rain events or rain coming in heavy downpours rather than slowly over the course of a day.

Common parlance recognizes that a drought is drought regardless of whether it is due to a change in the mean or a change in the variance. However, it is not hard to imagine that two areas with the exact same climatic means can have very different agriculture potential. An area with even rainfall and temperatures through the year could be the breadbasket of a Nation. If identical means conditions remained but precipitation fell in torrential downpours followed by months with no rain and temperatures varied from freezing to scorching, the region would become a wasteland as far as agricultural potential was concerned.

A major point in this discussion was to make clear that our method produces changes in extremes, but does not include changes in all aspects of a climate variability that affects the frequency of extremes (e.g., variance). The intent of this chapter is to address more specifically the impacts of variability, extreme events, and changes in variability.

We begin by briefly reviewing the evidence from climate modeling on how variability could change. We then review the impact of weather on variability in crop yields, followed by a discussion of possible future responses to changing variability. The impacts of climate change and variability are considered from the viewpoints of projecting extreme events, predicting the impact of climate variability and extreme events on crops, relating crop yield variability to climate, and the economic implications of potential ENSO shifts. The impacts of climate variability on the variability of U.S. corn, cotton, sorghum, soybeans, and wheat yields are examined. These crops were chosen because of their widespread coverage and important economic value. While other regionally important crops will also be affected by climate change and variability, space considerations preclude extensive discussion of them beyond brief mention.

4.2 Projecting Extreme Events

Most of our knowledge of possible changes in extremes comes from climate model experiments of the future with increased greenhouse gases and aerosols. Climate modeling capabilities have greatly increased in the past ten years, and it is more common now to examine the changes in at least certain types of extremes simulated in climate models than it was in the past. The current generation of coupled atmosphere-ocean general circulation models (AOGCMs) has improved spatial resolution (about 2.5 degrees latitude), adopted more realistic land surface schemes, and include dynamical sea ice formulations. These and other improvements, such as the nesting of high resolution (10s of km) regional models within AOGCMs, have improved our ability to estimate possible changes in some extremes. In this section we review what is known from climate models on possible changes in extreme events in the 21st century.

4.2.1 Temperature

One of the earliest and simplest analyses of possible changes in extreme events concerns that of increased frequency of the extreme daily high temperature events and a decrease in the frequency of low daily temperature events. With an increase in mean (maximum and/or minimum) temperature, assuming no other changes in other aspects of temperature (e.g., variability), there will be an increase in the likelihood of, for example, days with maximum temperatures exceeding 35º_C. The change in the probability of extreme daily temperature events is nonlinear with the change in mean temperature, i.e., a small change in mean temperature will produce a relatively large change in the probability of a temperature extreme occurring (Mearns et al., 1984). Changes in the variance of temperature also contribute to changes in the frequency of extremes, and on a per degree basis has a greater influence than the change in the mean (Katz and Brown, 1992). However, in climate model experiments investigated so far, the mean usually changes more than the variance.

It has been found in a number of climate simulations of the future that in the northern mid-latitudes, the daily variance of temperature increases in summer, but tends to decrease in winter. These changes complement the effects of the changes in mean, i.e., the increased frequency of high temperature events in summer are further increased by the increased variability, while the decreases in low extremes in winter are further decreased by the decreasing variance (Meehl et al., 1999).

4.2.2 Precipitation

Earlier studies of climate models found a tendency for increased precipitation intensities and this result continues to be found in recent studies. For example Zweirs and Kharin (1998) found that mean precipitation increased by about 4% and extreme return values increased by 11% over North America in a doubled CO_2 experiment. Another important and seemingly robust result from climate models is a tendency toward mid-continental drying in summers, due to higher temperature and reduced precipitation, with increases in CO_2 (e.g., Wetherald and Manabe, 1999). As discussed above, seasonal and regional changes in the pattern of precipitation and temperature are accounted for within the crop studies described in Chapter 3 and used as the basis for economic modeling. Thus, this general regional patterns and seasonal patterns are reflected in the regional estimates presented in that chapter although not the pure changes in variability.

4.2.3 Extratropical and Tropical Storms

While there have been steady improvements in the ability of climate models to adequately model tropical and extratropical storms, there remains relatively low confidence in model simulations of changes in these features. There are a growing number of studies addressing possible changes in extratropical storm activity but little agreement is found among these studies. Also, a consensus among global models of changes in the frequency or intensity of tropical cyclones has not emerged. Several studies have shown increased intensity of tropical cyclones, but the models are still too coarse to resolve many important features of such storms (e.g., the eyes of hurricanes).

4.2.4 El Niño Southern Oscillation

ENSO (El- Niño/Southern Oscillation) is a major coupled ocean-atmosphere phenomenon that determines the interannual variability of climate, and thus will be a major determinant of the future variability of climate. There are much improved simulations of ENSO in the current generation of climate models, but conclusive evidence of how ENSO might change remains elusive. Several studies, however, suggest that with a warmer base condition, precipitation extremes associated with El Niño events may become more extreme, i.e., more intense droughts and flooding conditions may be found (e.g., Meehl, 1996). In the realm of seasonal forecasting of ENSO events and its connections with broader climate phenomena, there has been considerable progress. The relevance of more severe ENSO events to agriculture is discussed below in section 4.3.1.

4.2.5 Conclusions

The literature on projecting extreme events indicates that our knowledge of changes in extreme climate events in the future remains limited, with the exception of relatively simple single variable extremes such as those related to daily temperature. Yet it is certain that many types of extreme events will change in frequency and possibly intensity in the future. Many of these (temperature and precipitation extremes, droughts, floods) have important effects on agriculture. Even with little certain information on exactly how such extremes may change, sensitivity analyses can illustrate how changes in extremes could affect cropping systems and agriculture in the US, suggesting strategies that reduce losses. While long-term prediction of changes in climate variability due to greenhouse gas accumulation may remain elusive, studies of response to variability are useful in identifying strategies that could be used as medium term climate prediction improves.

4.3 Predicting the Impact of Climatic Variability and Extreme Events on Crops

Most research regarding potential change in crop yield due to climate change has focused on the impacts of changes in long term climatic averages, with the assumption that the climate variability as technically defined will be the same as in the present climate. However, changes in climate variability will affect the frequency of extremes and could have important impacts on crop yields. We discuss below some of the effects of extreme events on agriculture (independent of whether their probabilities are changing), aspects of modeling extreme events in crop models, and the effect on interannual events such as ENSO. The next subsection discusses some of the recent efforts that have attempted to separate changes in variability from changes in the mean. Finally we discuss spatial variability.

4.3.1 Examples of Extreme Events Affecting Crops

Extreme events that affect crops occur on varying spatial and temporal scales. Events on the interannual time scale include seasonal droughts, floods, cold winters, etc. Well-known periods of drought in the 1930s and again in the 1950s severely decreased crop yields in the United States.

On time scales of hours to weeks, within the cropping season, very short-lived extreme events can cause serious damage to crops. For example, a number of field crops suffer after consecutive days of high temperatures during sensitive phenological stages. Corn is one of the more sensitive crops, and a number of researchers have identified damaging events: Shaw (1983) reported that damage to corn occurs after 10 days of high maximum temperatures during silking, while Berbecel and Eftimescu (1973) identified daily maximum temperatures above 32°C during tasseling and silking as being particularly damaging. Soybean, while less vulnerable than corn, can suffer from maximum temperatures exceeding 40°C at the onset of flowering (Mederski, 1983). Cotton plants abort bolls when the temperature exceeds 40°C for more than six hours, and in rice a temperature exceeding 30°C during anthesis causes spikelet sterility (Acock and Acock, 1993). Short-term moisture deficits can cause loss in yield depending on the phenological stage during which they occur. Most often reproductive stages are the most vulnerable. Excess precipitation also causes problems for crops in the form of lodging, lack of aeration, and increased insect pest infestation (Rosenzweig and Hillel, 1998).

Extreme cold events impact fruit and citrus. Freezing temperatures (below 0°C) during the winter months result in catastrophic damage to the citrus crops in Florida, Texas, and California. Extreme winter temperatures impact the more cold sensitive peach crop by killing the flower buds with temperatures below -18°C and killing the peach trees with temperatures below -30°C. A change in the frequency of these extreme events due to climate change could result in a contraction of the area these crops are grown if the extreme events occur more frequently, or an expansion of the production region with a less frequent occurrence of the extreme cold temperatures.

4.3.2 The Modeling of Extreme Events in Crop Models

In most crop models, the impact of temperature occurs on a daily basis. The simulation of temperature effects in crop models is almost always independent of the temperature of the preceding day. In other words, the impact of a warm day on growth is the same whether the day before was warm or very cold. Many of the models accumulate temperature stress days, based on both high and low prescribed threshold temperatures. Given the relative success of most crop models, this approach appears to work reasonably well.

Occasionally, crop models simulate more complex sequences of extremes. One example is the modeling of winter kill in some crop models (e.g., CERES-Wheat), which takes into consideration the hardening of the crop (based on temperature accumulation at some prescribed low temperature), and exposure to very low extremes (killing temperatures). If the crop experiences a rapid oscillation between high and low minimum temperatures, winter kill can result (e.g., Mearns et al., 1992).

Crop models are, however, in general less successful at modeling the effects of sequences of days, such as the effects of five consecutive days of above 35°C temperatures during silking in corn. The relatively small sample size of such events makes it difficult to successfully model the physiology of this effect. Being able to predict the effects of heat waves, for example, could be more important in a climate-changed world, where both the mean and variability of day-to-day temperatures increased. Current state-of-the art models likely underestimate the impact of the resultant extremes of climate on crop growth. Thus, while the altered climate scenarios we use create a greater likelihood of such heat waves, the existing generation of crop models lack the specific mechanisms to fully reflect these types of events.

On the other hand, crop models have long been constructed with a view toward modeling the effects of moisture stress (i.e., a deficit) on crops and are relatively successful at this. However, important differences in the details of how moisture stress is modeled can result in very different responses of crop models to the same climate change conditions. For example, as noted earlier, the sensitivity of crops to moisture stress tends to be growth-stage specific. While most crop models use the accumulated degree-day approach to represent the progressive phenology through a crop season, they can differ substantially in how detailed this treatment is. EPIC, for example, has a relatively crude phenological submodel, while the CERES family of crop models tends to represent more detailed phases of phenological development. In a comparison of the response of CERES maize and wheat with EPIC maize and wheat for climate change scenarios in the Great Plains Mearns et al. (1999) found that the models predicted different magnitudes and directions of change in yield, primarily due to the differences in when (phenologically) the simulated crops experienced moisture stress.

While moisture deficit (drought) has been the principal concern of crop modeling efforts, excess moisture also causes significant crop damage. Some crop models (such as EPIC, Williams et al, 1989) do include the modeling of stress due to insufficient aeration, and at least one of the CROPGRO models (SOYGRO, Boote et al, 1998) includes an excess moisture factor. However, there is little information on how realistically these models simulate excess moisture effects.

Infrequent combinations of weather variables can also lead to unusual crop responses. For example, moisture or high humidity after physiological maturity has been reached in combination with warm temperatures can cause grain to germinate or sprout before harvest. Water logging in combination with warm temperatures in spring can have particularly negative impacts on crop growth. The impacts of these interactions are often not simulated by crop models. For example, as noted above, the EPIC model calculates an aeration stress factor based on the water content of the top 1 m of soil, but this factor is not dependent on temperature.

Overall, a major direction of crop modeling is to be able to understand crop response to varying climate. Climate can vary in many dimensions and not all of the potential effects are captured. Moreover, most of the testing and validation of crop models occurs in areas where these crops are grown. While annual variability in climate creates a rich set of weather conditions against which to evaluate these models, climate change could produce combinations of climatic conditions that are only infrequently observed where these crops are currently grown and, thus, our ability to capture these effects may be limited. Direct comparisons of different models of the same crops to the same climate conditions can produce widely varying results and running a crop model at a new site can require considerable calibration before it can estimate realistic yields at the site. Overall, crop models are able to capture fairly well some of the broad changes and on average perform well. As we move to consider more detailed aspects of climate and attempt to make more precise predictions of how to respond to very specific climate conditions we require more detailed models, experimental evidence, and site level verification that the model can reproduce actual responses to varying conditions.

4.3.3 Inter-Annual Variability: ENSO events

An example of an increase in climate variability on an inter-annual scale would be if precipitation extremes associated with the El Niño phenomenon become even more severe than they are currently. Our understanding of the influence of the El Niño-Southern Oscillation (ENSO), as well as other important couplings of ocean currents and atmospheric dynamics, on climate variability in specific regions has greatly increased in the last decade. This development has enhanced our ability to forecast events such as El Niño and La Niña years on a regional basis.

The general impacts on crop yield of the climate regimes associated with the El Niño phenomenon are reasonably well understood and effectively captured in a number of different crop simulation models. These models have been used to determine the specific components of the climate that are responsible for yield variations. For example, a recent study of the impact of El Niño events on corn yield in the US corn belt using crop growth simulation indicated that water stress in July and August is the primary cause of lower corn yields in La Niña years, along with a shorter period of grain filling due to high temperatures (Phillips et al. 1999). The cooler temperatures and greater rainfall during El Niño years had less pronounced impact on yield than the dryer, warmer La Niña years.

Studies have also been undertaken to determine the value of El Niño forecasting to agriculture at both the farm management and industry level. A fixed management strategy for nitrogen fertilizer application rate and cultivar selection in a wheat cropping system in Australia was compared to a tactical strategy that depended on the seasonal forecast using the Southern Oscillation Index (Hammer et al. 1996). An analysis of simulated results using the tactical strategy indicated significant increases in profits and reductions in risks compared to the fixed management strategy. In another Australian study, phases of the Southern Oscillation Index were used to make forward estimates of regional peanut production (Meinke and Hammer 1997). Because peanut yield varies greatly with rainfall, high variability in rainfall is of concern to peanut processors and marketers. One conclusion of this study was that the industry could profit by using yield forecasts made three to five months ahead of harvest to strategically adjust for expected volume of production.

The studies reported above were conducted to evaluate the extent to which advanced warning of an El Niño or La Niña events, as well as other important couplings of ocean currents and atmospheric dynamics, can significantly improve farm and agricultural industry management decisions. As these types of analyses improve, our ability to predict the impacts of changes in decadal scale climate variability on agriculture will be enhanced. Future studies should take into account, on a regional basis, the current agricultural systems and feasible alternative systems in the context of current and possible future economic and policy environments. This type of approach, linked with appropriate climate scenarios, should be useful in predicting the sensitivity of agricultural systems to changes in decadal scale climate variability.

4.3.4 Intra-annual Variability (Weather)

Climate change may also cause changes in the within-season variability of temperature and precipitation, although the assumption in most studies of agricultural yields under future climate change scenarios has been that the nature of this variation will be the same as in the present climate. However, there could be important impacts if within season variability increases. Such change would further shift the probability of extreme events and might also have less obvious influences on crops, such as changing the rate of development.

4.3.4.1 Changes in variability alone

Several studies encompassing a variety of crop simulation models and regions have systematically investigated the impact of changing within season variability of temperature and precipitation (Mearns et al., 1996; Riha et al., 1996). General conclusions from these studies are that as temperature variability increases crop yield decreases, and that the capacity of the soil to store water strongly mediates crop response to changes in precipitation variability. Not surprisingly, sandy soils are far more vulnerable to increases in rainfall variability.

In an extension of the Mearns et al. (1996) analysis, Rosenzweig, Mearns, and Goldberg (study done for this report) continued their investigations of climate variance change on CERES-maize and SOYGRO crop models for three locations in the Corn Belt (Grand Island, NE; DesMoines, IA; Indiannapolis, IN). Their results confirmed those of Riha et al. (1996) who applied EPIC corn and soybean models. Increased variability of temperature or precipitation resulted in substantially lower mean simulated yields, while decreased variability of temperature produced insignificantly small increases in yield. The implications of this asymmetric response to variability in temperature is that relatively low variability in temperature is one of the major factors making these corn belt areas so productive. The year-to-year variability of yields was also increased by increased variability of temperature and precipitation. The implication for climate change is that the main risk to these regions is likely to be the potential for increased variability.

4.3.4.2 Combined effects of mean and variability changes.

Several studies (e.g., Mearns et al., 1997; Semenov and Barrow, 1997) have examined the effects of climate change scenarios that included changes in both the mean and variance of climate on simulated crop yields by altering parameters of stochastic weather generators. In both studies, the negative effects of the impacts of climate change on crops were exacerbated by including the effects of changes in climate variability.

4.3.5 Spatial Dimensions of Extremes

Extreme events can have spatial characteristics that have implications for appropriately simulating their impact on crops yields over relatively large spatial and temporal scales. Some extreme events are common when large areas are being considered, but only occur infrequently in a specific location, e.g., hail. Hail causes damage that can lower yield, and in the case of horticultural crops, lower the value of the crop. For a given location (such as an experimental farm) where data for crop model development and testing are being generated, the likelihood of hail occurring in any given growing season may be quite low. Therefore, the impact of such a phenomenon is not considered in the simulation of climate impacts on crop yields. Clearly, if the frequency of occurrence of such a phenomenon were to increase, it would cause damage to a larger proportion of the cropped area and might reach a point where regional yields were significantly affected.

Some extreme events, rather than occurring randomly over an area, are more likely to occur in certain areas due to the interactions of weather with the landscape. Examples include cold air drainage creating frost pockets, gusting winds causing lodging, snow pack of variable depth affecting the winter survival of wheat, and flooding. Some current crop models can simulate the impact of such events on both crop growth and field operations, but the more difficult challenge is to predict the spatial extent of these events from terrain and weather data. This variability of the spatial dimension is usually not explicitly included as input to crop models. For example, most agronomic crops are not able to survive flooding. Changes in precipitation resulting in more rain occurring during short periods of time could lead to more flooding, but clearly the likelihood and extent will depend on terrain factors, as well as flood management policies.

4.4 Response of Future Crops to Extreme Events/Climate Variability

4.4.1 Adaptation to Temperature Extremes

Crop varieties have been developed to avoid temperature extremes through selection of plants that can complete their life cycle more quickly than traditional varieties. In temperate climates, these varieties can be planted late and harvested early in order to avoid chilling and frost injury. In tropical climates, these varieties can be used to avoid periods of high temperatures. This type of adaptation is generally well simulated by crop models. Increases in temperature variability alone would be expected to further reduce the length of the growing season and therefore require growing a shorter season variety or crop. However, for many crops, varieties have been developed that can tolerate (not just avoid) heat and cold. This type of adaptation is somewhat more difficult to simulate, because tolerance is often limited to a particular stage of development, such as germination, emergence, flowering and grain ripening. These adaptations, though limited, can have significant impact on growth and yield. For example, the ability for a seed to germinate at even a few degrees cooler temperatures can in many cases significantly increase the region in which the crop can be grown. Breeding for cold tolerance during germination and heat tolerance during grain filling will likely mitigate some impacts of increases in temperature variability and some extremes. Crop simulation models vary in their ability to simulate these varietal adaptations.

It is important to realize that while selected varieties may, during specific life stages, tolerate temperature extremes better than more traditional varieties, if the mean seasonal temperature moves outside the optimum range for the crop, then yield of all varieties generally decreases significantly. In general, varieties that yield the best under non-stressful environments also yield the best, though the yield is reduced, under stressful environments (Evans 1993). This suggests that current breeding strategies will be useful in selecting plants that can perform reasonably well even if temperature variability increases.

4.4.2 Adaptation to Drought

Similarly, crop varieties have been developed to avoid drought through selection of plants that can either complete their life cycle more quickly than traditional varieties or that are not in phenological stages sensitive to stress (such as flowering) when drought is likely to occur. It is less clear that the ability of plants to tolerate drought stress has been significantly improved in the course of plant breeding, except that breeding for tolerance of high temperatures may improve yield under drought. The water use efficiency (WUE) of crops, when expressed as the ratio of biomass of crop produced per unit mass of water transpired, is lower in very warm climates compared to more temperate climates.

4.5 Empirical Estimates of Crop Yield Variability as Related to Climate

Another approach for evaluating the impact of variability on crops is to use cross section evidence. The availability of state level detailed climate and yield data across the U.S. allows the examination of how year-to-year and region-to-region climate variation alters crop yields. Such a study was done by Chen et al. (1999b) as part of the agricultural sector assessment. Variability influences of climate were investigated using USDA-NASS (1999) Agricultural Statistics state level yields and acreage harvested for 25 years (1973 to 1997). State-level climate data matched to the agricultural output data were drawn from the NOAA(1999) which includes time series observations for thousands of weather stations. The April to November average temperature for the published weather stations in a state was used.

The approach relies on the ability to separate changes in variability from changes in means, the details of which are provided in Chen et al., 1999b. The basic results are in terms of elasticities, that is how does a 1% change in the temperature or precipitation affect yields in percentage terms. We are able to estimate how the 1% change in climate affects both the mean yield and the variability of yield. Results can vary depending on the functional form of the estimated equation.

Table 4.1 reports the mean yield elasticity estimates for both a linear and multiplicative (the specific form is commonly known as a Cobb-Douglas production function in economics) functional form. In terms of changes in the mean, the sign on precipitation is positive for the corn, cotton, and sorghum crops and is negative on temperature. This indicates that crop yields increase with more rainfall and decrease with higher temperatures. Elasticities for the soybean and wheat crops are mixed. Sorghum showed the highest elasticities for both rainfall and temperature.

The impact of climate change on variability is reported in Table 4.2. In terms of variability, the clearest results are obtained for corn, cotton and sorghum. The results are the same for both functional forms tested. Increases in rainfall decrease the variability of corn, cotton, and wheat yields. Corn yields are predictably more variable with higher temperatures. Cotton and sorghum rainfall variability elasticities are all small, with a one percent increase in rainfall leading to a half of one percent or less increase or decrease in yield variability. Cotton and sorghum have high temperature variance elasticities with a one percent increase in temperature producing up to an eleven percent decrease in yield variability. Similarly large elasticities are obtained for rainfall effects on corn and wheat yield variability. All of these results are consistent across functional forms. Soybean elasticities are all less than one, but sign inconsistency across functional forms confound interpretation of these results.

We used regional estimates of climate change arising under the Canadian and Hadley Center climate model simulations to estimate whether, based on these climate projections and the statistical models estimated here, crop yield variability would increase or decrease using only Cobb-Douglas form. The results are given in Table 4.3 and show fairly uniform decreases in corn and cotton yield variability with mixed results for other crops. Wheat yield variability tends to decrease under the Hadley Center climate and increase under the Canadian climate model. Soybean yield variability shows a uniform increase with the Hadley Climate Change Scenario.

The basic conclusion is that these mean climate changes can potentially produce fairly large changes in variability but these can be either increases or decreases. This analysis considers only the potential for changes in the mean climate conditions to change yield variability and does not consider how changes in climate variability itself might affect either mean yields or the variability of yields.

4.6 Estimates of the Economic Implications of Potential ENSO Shifts

Some argue that global climate change may alter the frequency and strength of extreme events. One marker for extreme events that has recently received considerable public attention is the El Niño-Southern Oscillation (ENSO) climatic phenomenon. Timmermann *et al.* (1999) recently presented results from a climate modeling study implying that global climate change would alter ENSO characteristics causing

- the mean climate in the tropical Pacific region to change towards a state corresponding to present day El Niño (warm) conditions;
- stronger inter-annual variability with more extreme year-to-year climate variations;

and

- more skewed inter-annual variability with strong cold events becoming more frequent.

There is much debate about these results. We use them here to illustrate the sensitivity of agriculture to such shifts. Details of the analysis are provided by Chen et al. (1999a), a study conducted as part of the agriculture sector assessment. The analysis examined the economic implications of a shift in ENSO frequency and intensity using the quantitative definition of the shift as developed by Timmermann et al. (1999). Specifically, estimates of the economic consequences of shifts in ENSO frequency and strength on the world agricultural sector are described.

According to Timmermann et al. (1999), the current probability of ENSO event occurrence (with present day concentrations of greenhouse gases) is 0.238 for the El Niño phase, 0.250 for the La Niña phase, and 0.512 for the Neutral (non El Niño - non La Niña) phase. They then project that the probabilities for these three phases, under increasing levels of greenhouse gases, will be 0.339, 0.310, and 0.351 for El Niño, La Niña and Neutral, respectively. In other words, they project that the frequency of both the El Niño and La Niña phases to increase, while the frequency of the neutral phase frequency would decrease. While not offering specific evidence, they argued that such a frequency change could be expected to have strong ecological and economic effects.

Our analysis investigates more formally and quantitatively whether such a change would have strong economic impacts on the agricultural economy. ENSO events have been found to influence regional weather and, in turn, crop yields. Several studies have estimated the value of farmers adapting to ENSO events, that is, if farmers knew ahead of time the ENSO phase what could they do to improve their economic outcome compared to the situation where they operated only on long-term average climate conditions. Results indicate that there is economic value to the agricultural sector in using information on ENSO events. In terms of aggregate U.S. and world economic welfare, the estimates of using ENSO information in agricultural decision making have been in excess of $300 million annually.

The model experiment conducted to study these events involve different assumptions about the information with which farmers operate. To consider the value of knowing which event would occur two fundamentally different situations were simulated in the ASM model. These were:

1. Producers were assumed to be operating without use of any information concerning ENSO phase and thus choose a crop plan (set of crops to be planted on their land base) that represents the most profitable crop mix across a uniform distribution of weather events based on data for the past 22 years. We refer to this as the "Without use of ENSO Phase Information" Scenario.
2. Producers were assumed to incorporate information regarding the pending ENSO

phase and thus choose a set of crops that is the best performer economically across that individual phase. Thus, crop mixes which are optimized for ENSO events are selected across a distribution of the five ENSO states, as are crop mixes for the other states. Initially, the strength of each ENSO is assumed to be equally likely. This analysis is called the “With use of ENSO Phase Information” Scenario.

In addition to structuring the analysis to vary the response of farmers to ENSO information, a second key component is varied in the model experimentation. In particular, three ENSO phase event probability conditions are evaluated.

- The first represents current conditions with respect to the probability of each phase. Specifically, we assume El Niño phases occur 0.238 of the time, La Niña with a probability of 0.250 and 0.512 for Neutral. Within an El Niño phase, we assume that individual crop yields for five El Niño weather years contained in our data set are each equally likely (i.e, same strength), with a comparable assumption for the four La Niña events and the 13 Neutral yield states.
- The second incorporates the frequency shifts suggested by Timmermann et al. (1999). Here the El Niño phase occurs with a frequency of 0.339, the La Niña phase 0.351 and the Neutral phase 0.310. Within each of the phases we again assume the cropping yield data states are equally likely.

The third considers the impact of stronger or weaker ENSO events. The three event types above were reclassified into five different ENSO event: (1) Strong El Niño, (2) Weak El Niño (3) Neutral, (4) Weak La Niña, and (5) Strong La Niña.

- The frequency shifts used in this experiment are those from Timmermann et al. (1999) as computed above. To evaluate event strength shifts, we assume that the stronger El Niño and La Niña events occur with a 10 percent higher frequency. Specifically, if the 1982-1983 and 1986-1987 El Niños occur each with a 0.20 probability within the set of five El Niño events observed in the data set, above (assuming a uniform distribution across the five observed El Niño’s in our data set) we shift those probabilities to 0.25 and reduce the probabilities of the three other El Niño years to 0.167. Similarly, the two strongest (in terms of yield effects) La Niña events have their probabilities raised to 0.30 from 0.25, while the weaker two La Niñas have their probabilities reduced to 0.20.

The results of this analysis appear in Tables 4.4 and 4.5. In Table 4.4 estimates are provided of aggregate economic welfare before and after the ENSO probability shifts. Table 4.5 contains a more disaggregated picture of these economic effects. The economic consequences are evaluated for both situations regarding producer decision-making (ignore or use the ENSO forecasts). As in Chapter 3, the economic effect is measured in terms of changes of welfare. The aggregate changes in Table 4.4 are the sum of domestic consumer, domestic producer, and foreign surplus. Table 4.5 provides a breakdown of these results between producers, consumers, and foreign interests. Four major results can be drawn from this work.

- First, an increase in ENSO event frequency and intensity causes significant increases in crop losses. Specifically, the welfare loss due to the frequency shift where farmers operate without information on ENSO event probability (comparing the first and second rows of the first column of Table 4.4) is estimated to be $323 million. When both frequency and strength shifts are considered (i.e., comparing the first and third rows) the welfare loss increases to $1,008 million. This is about 5 percent of typical U.S. agricultural net income or about 0.15 percent of total food expenditures in the U.S. The strength shift, if more substantial than the one assumed here, could have substantially larger effects.

- Second, there is considerable value of farmers operating with better information about ENSO events and the value increases if the frequency and intensity of these events increase. Comparing the "with and without ENSO information" columns of Table 4.4 the value of ENSO forecasts under current ENSO frequency and strength is estimated at $453 million. This value is very similar to previous work as estimated by Solow et al. (1998). The value of ENSO forecasts increases to $544 million with the frequency shift and to $556 million if both frequency and intensity shift.

- Third, the additional damage due to these more intense and frequent ENSO shifts is not fully offset by better forecasting. The forecasting gains are greater with a more frequent and stronger ENSO than under the current ENSO frequency and strength but the gains do not offset the losses due to the ENSO shifts. The use of ENSO forecasts mitigates some of the negative economic effects of the shift. Specifically, the figures in parentheses in (Table 4.4, column 2) show an increase in damage from the current ENSO event frequency and intensity of $323 and $905 million.

- Fourth, there are both winners and losers from changes in ENSO frequency and intensity (Table 4.5). Specifically, the total welfare loss due to the shift in ENSO frequencies results in domestic producer and foreign country welfare losses but gains to domestic consumers. Most of these welfare losses occur in the foreign markets. These differences across groups arise from changes in U.S. and world prices for the traded commodities. For example, for the commodities evaluated here, there are price declines due to slight increases in world-wide trade when phase frequency shifts. The price declines result in losses to producers and exporting countries but gains to consumers.

In summary, these findings show extreme event frequency shifts should be of concern. The referenced ENSO case of Chen et al (1999b), that is summarized here, confirms the Timmermann et al. (1999) analysis that climate change induced shifts in ENSO frequency will have economic consequences. We further find that those consequences involve changes in both the level and variability of agricultural prices and welfare. Prices and welfare fall but these effects are reduced as producers anticipate and react to forthcoming El Niño and La Niña events. The projected changes of Timmermann et al. (1999) can be partly offset by producer reactions to ENSO information. If ENSO strength also intensifies, larger gains can arise by avoiding the effects of climate change that trigger the shifts. Again, we caution that there is much uncertainty and controversy with regard to whether or how global climate change would affect ENSO. Our intent here was simply to consider the ENSO shifts as a "what if" scenario.

4.7 Implications

The importance of extreme events in the context of the impacts of climatic change and variability on agriculture has received increased attention in recent years. Extreme events and climate variability have documented impacts on agriculture. Farmers have many financial mechanisms with which to address variability and extreme events ranging from crop insurance, and savings to forward contracting and an emerging market for weather derivatives. They can also change production practices to make themselves less vulnerable to variability. But, these are not able to eliminate the real effects on costs of variability, and in the case of financial mechanisms such as insurance and forward markets, the costs of variability are merely pooled or spread, not eliminated or reduced. As demonstrated by analysis of possible changes in ENSO events, better forecasting can reduce the effects of increased variability but cannot eliminate the additional costs.

The greatest limitation in the understanding of the impacts of variability on agriculture is the very limited ability to predict how variability will change. Our knowledge regarding possible shifts in the frequencies of extreme events with a new climate regime is limited. There also remains work to be done to incorporate the current information on changes in variability, as represented in climate models, into methodss for assessing impacts on agriculture.

It is important to distinguish among the relevant time scales and spatial scales of extreme events important to agriculture. In general crop models adequately handle extreme events that are longer than their time scale of operation. For example, crop models operating on a daily time scale can simulate fairly well the effects of a seasonal drought (lasting a month or more), but they will have more difficulty properly simulating responses to very short term extreme events, such as daily temperature or precipitation extremes. Another difficulty for crop models is properly representing composite extreme events such as a series of days with high temperatures combined with precipitation extremes. Therefore, in considering the possible effects of extremes and climate variability on crops from a policy point of view, extreme caution must be exercised in interpreting the analyses of climate models on what types of changes in extremes might occur in the future and in interpreting the responses of crop models to extreme climate events. However, it is expected that research in these areas will continue to develop rapidly.

While it is impossible to predict the future climate with great accuracy, the analysis present in this chapter provides an indication of the most favorable and least favorable future climates. For corn a wetter and cooler climate is the most favorable, while a hotter and drier climate is the least favorable resulting in decreased yield and greater year-to-year yield variability. A wetter and warmer climate would result in the greatest decrease in the year-to-year yield variability, conversely a drier and cooler climate would result in increased year-to-year yield variability. Sorghum year-to-year yield variability would be reduced most by a drier and warmer climate.

The United States consumer wins in the case of a future climate with a change in the ENSO phase frequency and an ENSO phase frequency shift with a change in the strength of the phases. Agricultural producers, on the other hand, are losers due to lower prices for their crops. Foreign interests also lose. The United States is generally a winner when both producers and consumers are considered. This analysis does not include all the potential effects of changes in the climate, which, when added together, may have more profound effects on agricultural production than the changes to the ENSO phase frequency and phase frequency shift. Again, the ENSO shifts are based on a single study and there remains much uncertainty about how global climate change would affect ENSO.

Overall, this chapter documents many of the ways in which variability can affect crops and how it may change in the future. The difference in terms of agricultural productivity between a moderate and even climate and one of extremes of hot and cold, wet and dry can be stark. The climate modeling community still has little capacity to predict climate with the resolution one would need to understand fully the implications for agriculture. There also remain challenges for the agricultural assessment community in evaluating the impacts of variability changes.

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Table 4.1 Response of Mean Crop Yields to Changes in Means of Climate Variables.

Production Function Form	Corn Precipitation % Change	Corn Temperature % Change	Cotton Precipitation % Change	Cotton Temperature % Change	Sorghum Precipitation % Change	Sorghum Temperature % Change	Soybean Precipitation % Change	Soybean Temperature % Change	Wheat Precipitation % Change	Wheat Temperature % Change
Linear	0.3273	-0.2433	0.0371	-1.5334	2.8844	-2.0866	-0.2068	0.0002	-0.1309	-0.5076
Cobb-Douglas	1.5148	-2.9792	0.4075	-0.7476	1.8977	-2.6070	0.34640	N.S.	1.4178	-0.3721

Key: N.S. not significant.

Table 4.2. Response of Crop Yield Variability Changes in Climate.

Yield Variability Function	Corn Precipitation	Corn Temperature	Cotton Precipitation	Cotton Temperature	Sorghum Precipitation	Sorghum Temperature	Soybean Precipitation	Soybean Temperature	Wheat Precipitation	Wheat Temperature
Linear	-9.7187	7.5058	-0.3028	-10.9386	0.5230	-5.3517	-0.7932	-0.2739	-2.1572	-0.1035
Cobb-Douglas	-1.4461	0.8923	-0.0212	-3.5800	0.4802	-2.5633	0.8194	0.0586	-1.6473	5.0875

Table 4.3. Percentage Increase in Crop Variability for 2090 Year by Scenario.

	Canadian Climate Change Scenario					Hadley Climate Change Scenario				
	Corn	Soyb.	Cott	Wht	Sorg	Corn	Soyb.	Cott	Wht	Sorg
CA			-12.84					-11.81		
CO				34.43					-10.60	
GA			-10.35					-6.92		
IL	-25.71	21.28				-24.73	18.90			
IN	-8.73	8.06				-26.31	20.30			
IA	-36.89	33.14				-26.83	20.90			
KS				-14.39	-0.75				-18.16	3.38
LA			-13.03					-7.97		
MN		4.01					10.60			
MT				32.86					-6.36	
MS			-13.92					-7.73		
NE	15.30	-4.74		48.22	-16.15	-15.05	11.65		-5.57	-1.72
OK				16.34	-9.27				-17.07	2.83
SD	-21.75			-6.94		-24.37			-19.10	
TX			-13.21	27.86	-10.83			-8.05	2.26	-3.10

Table 4.4. Aggregate Economic Welfare Comparisons under Shifts in ENSO Frequencies.

	Without use of ENSO information	With use of ENSO information	Gain of use of ENSO information
	(millions of U.S. dollars)		
Current probabilities	1,458,947	1,459,400	453
Phase frequency shift	1,458,533 (-414)	1,459,077 (-323)	544
Phase frequency and strength shift	1,457.939 (-1008)	1,458,495 (-905)	556

Note: The value in the ( ) represents the difference with respect to current probabilities due to the ENSO frequency and possibly strength shift.

Table 4.5. Welfare, by Component, With Use of ENSO Information.

	Current probabilities	Phase frequency shift	Phase frequency and strength shift
		(millions of U.S. dollars)	
Producers	35,883	35,576 (-307)	35,562 (-321)
Consumers	1,175,699	1,176,290 (591)	1,176,025 (326)
Foreign interests	247,818	247,211 (-607)	246,908 (-910)
Total	1,459,400	1,459,077 (-323)	1,458,495 (-905)

Note: The value in the ( ) represents the difference with respect to current probabilities due to the ENSO frequency and possibly strength shift.